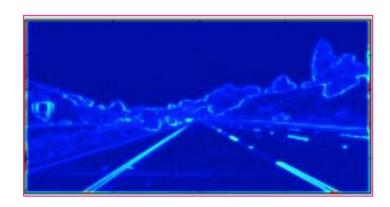
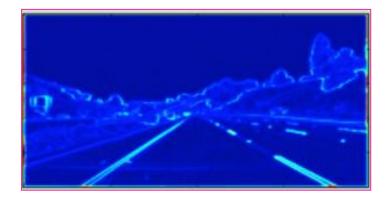
# Edge: Hough transform

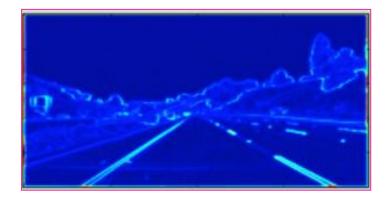
Dr. Tushar Sandhan



- Edges so far (operators, Canny)
  - o consider prior info about gradient behaviour
  - o do not consider anything about object shape, structure
  - o how did we get clear boundary edges previously?

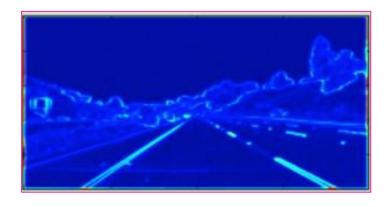


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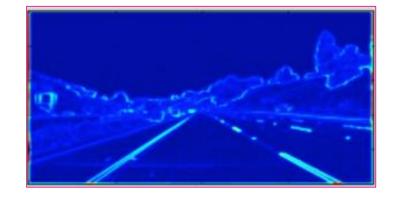
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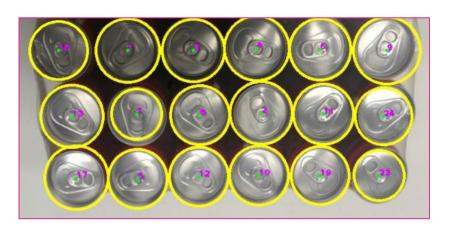
**J**•Linking



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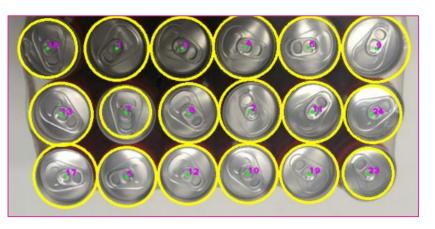
**J**•Linking

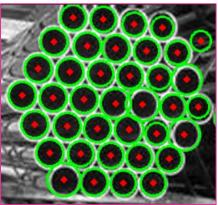


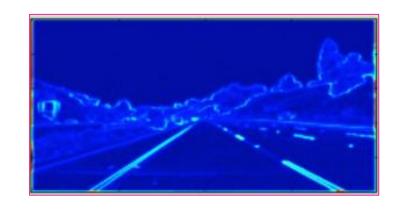


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**J**•Linking

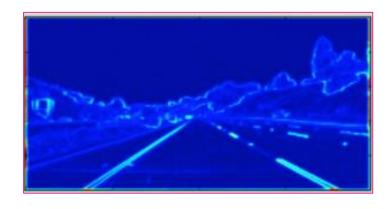


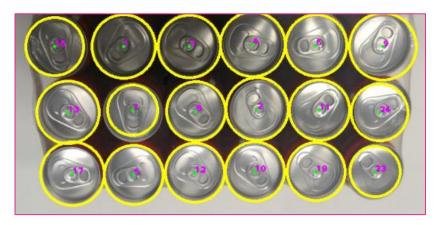


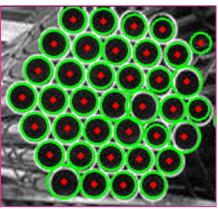


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**J** • Linking



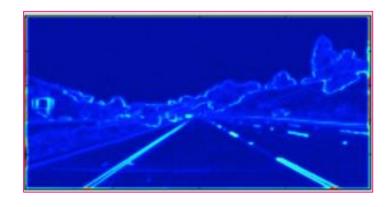


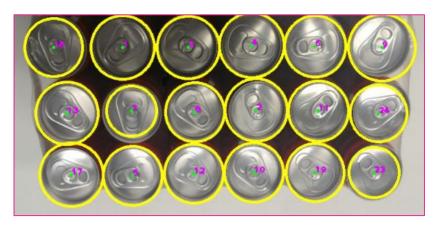


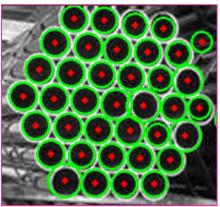


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  - o consider prior info about gradient behaviour
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**J**•Linking











- Image derivatives
  - o input image f(x, y)
  - o (optional) smoothed  $f_s(x, y)$
  - o get the gradients  $g_x(x,y)$ ,  $g_y(x,y)$
  - $\circ$  get thresholded edge map  $M_T$

$$G(x,y) = e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

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$$g_x(x,y) = \partial f_s(x,y)/\partial x$$
  $g_y(x,y) = \partial f_s(x,y)/\partial y$ 

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$$g_x(x,y) = \partial f_s(x,y)/\partial x$$

$$g_{y}(x,y) = \partial f_{s}(x,y)/\partial y$$

$$M_s(x,y) = \|\nabla f_s(x,y)\| = \sqrt{g_x^2(x,y) + g_y^2(x,y)}$$

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$$\alpha(x,y) = \tan^{-1} \left[ \frac{g_y(x,y)}{g_x(x,y)} \right]$$

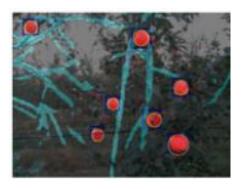
- Hough transform (HT)
  - o considers shape of the object as prior info.
  - o shape is defined as a function and parametrized

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- Shape detection
  - plat fruits
     plucking
     autonomous
     robots

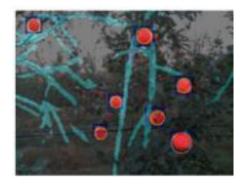
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  - o considers shape of the object as prior info.
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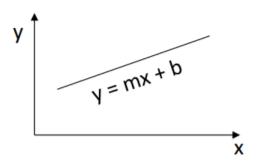


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  - shape is defined as a function and parametrized

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  - plat fruits plucking autonomous robots

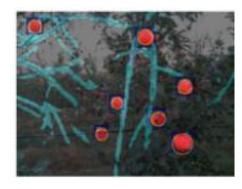


Lines

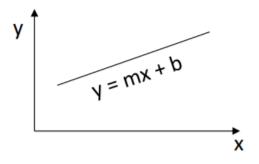


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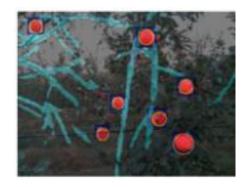
Lines



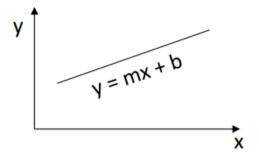
Hough Transform

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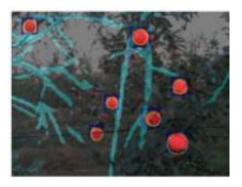
Lines



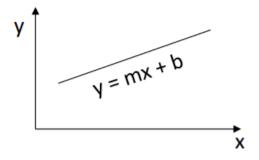
- Hough Transform
  - a space of parameters

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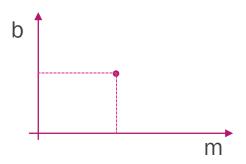
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Lines

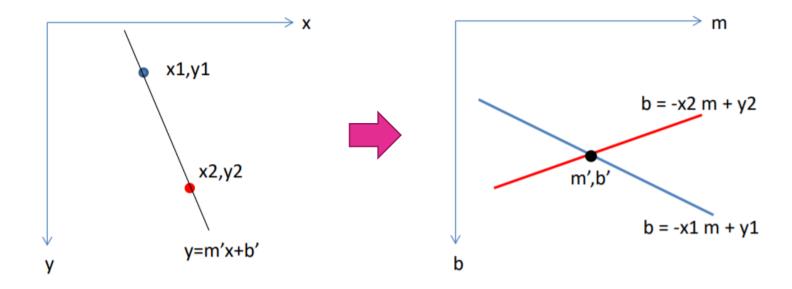


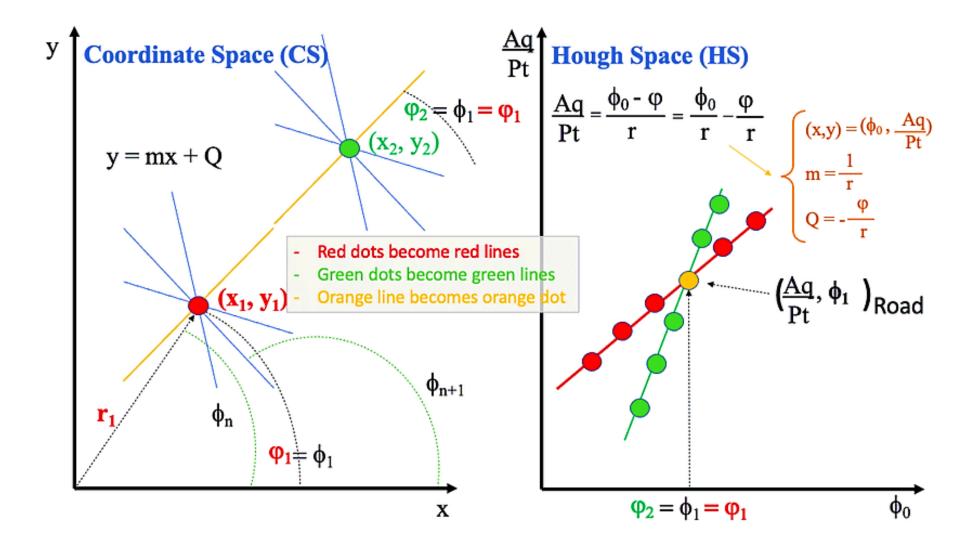
- Hough Transform
  - a space of parameters



- Hough transform duality
  - Lines in the image space becomes a point in the Hough space
  - A point in the image space becomes \_\_\_\_\_ in the Hough space

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  - A point in the image space becomes \_\_\_\_\_ in the Hough space



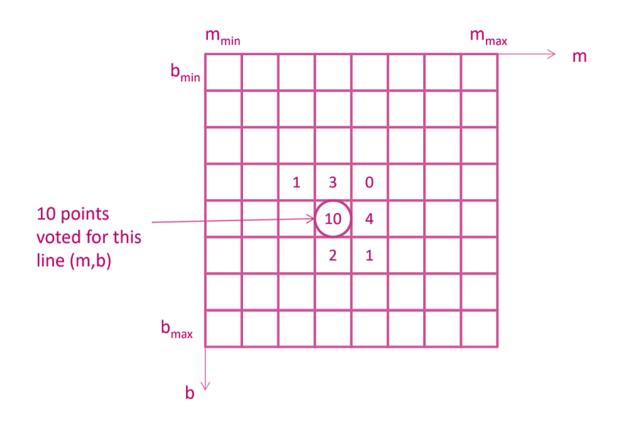


Hough space voting

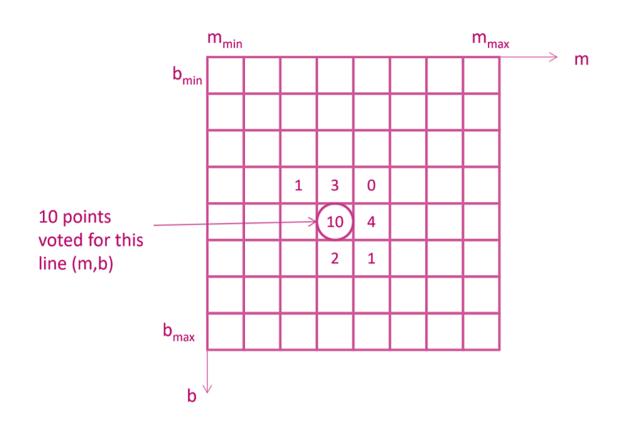
courtesy: W. Hoff

- Hough space voting
  - o initialize accumulator A(m,b) → 0

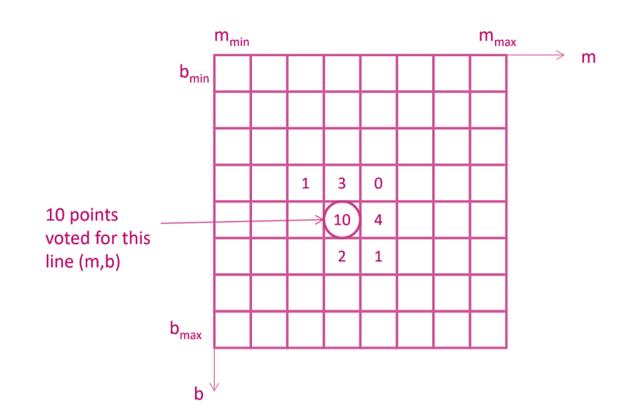
- Hough space voting
  - o initialize accumulator  $A(m,b) \rightarrow 0$



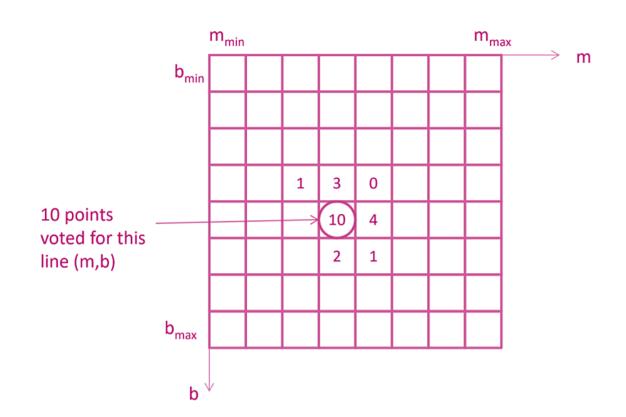
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  - o initialize accumulator A(m,b) → 0
  - o for each edge element, increment all cells that satisfy b = -xm + y



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  - o initialize accumulator  $A(m,b) \rightarrow 0$
  - o for each edge element, increment all cells that satisfy b=-xm+y
  - o local maxima in A(m,b) correspond to lines



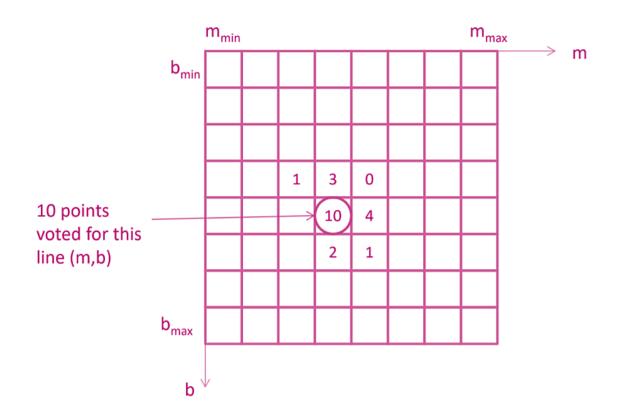
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  - local maxima in A(m,b) correspond to lines
    - is there any issue here?



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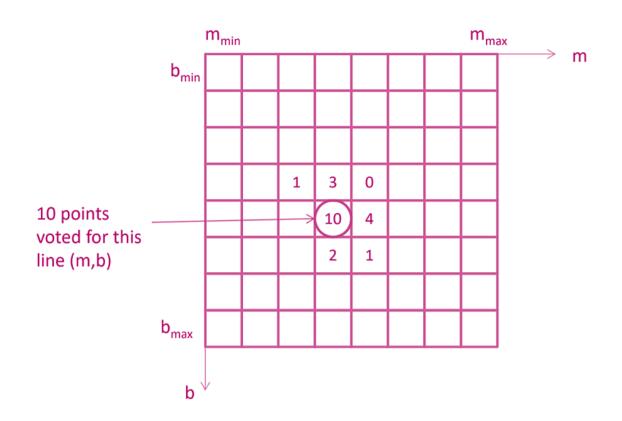
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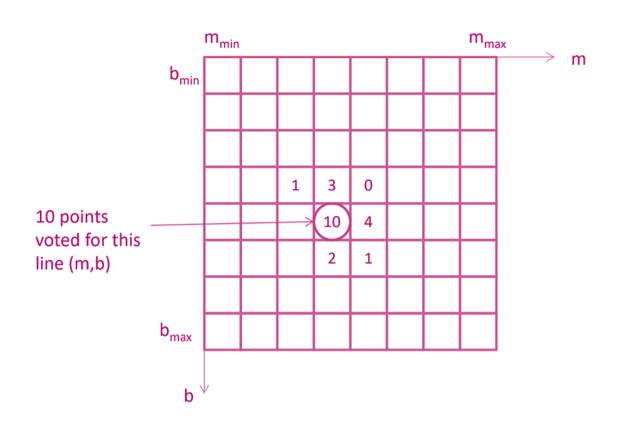


- Hough space voting
  - o initialize accumulator  $A(m,b) \rightarrow 0$
  - o for each edge element, increment all cells that satisfy b = -xm + y
  - local maxima in A(m,b) correspond to lines
    - is there any issue here?
    - for vertical lines

ī



- Hough space voting
  - o initialize accumulator  $A(m,b) \rightarrow 0$
  - o for each edge element, increment all cells that satisfy b = -xm + y
  - local maxima in A(m,b) correspond to lines
    - is there any issue here?
    - for vertical lines
      - $M \rightarrow \infty$

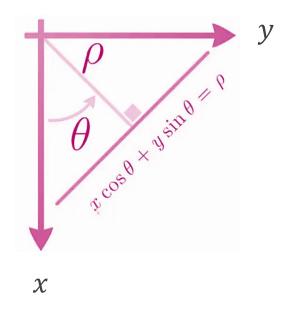


Horizontal lines

$$\theta = 0^{o}$$

Horizontal lines

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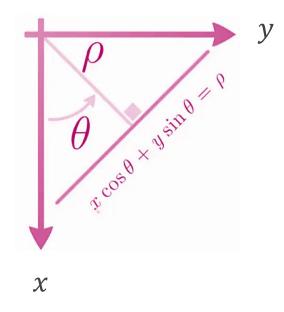


Horizontal lines

$$\theta = 0^{o}$$

Vertical lines

$$\theta = 90^{\circ}$$



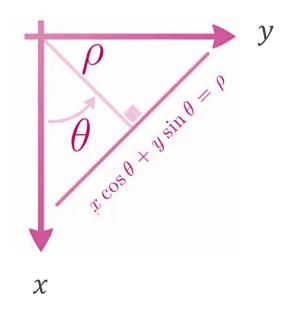
Horizontal lines

$$\theta = 0^{o}$$

Vertical lines

$$\theta = 90^{\circ}$$

- Ranges:
  - $\theta$  ∈ [−90°, 90)
  - $\rho \in [-dmax, +dmax]$
  - o dmax?



EE604: IMAGE PROCESSING

Horizontal lines

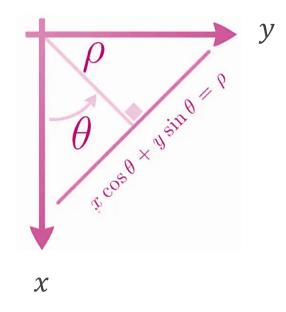
$$\theta = 0^{o}$$

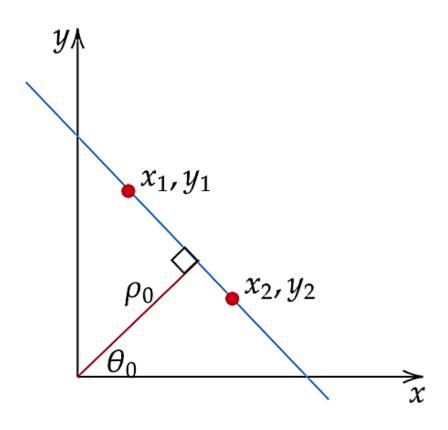
Vertical lines

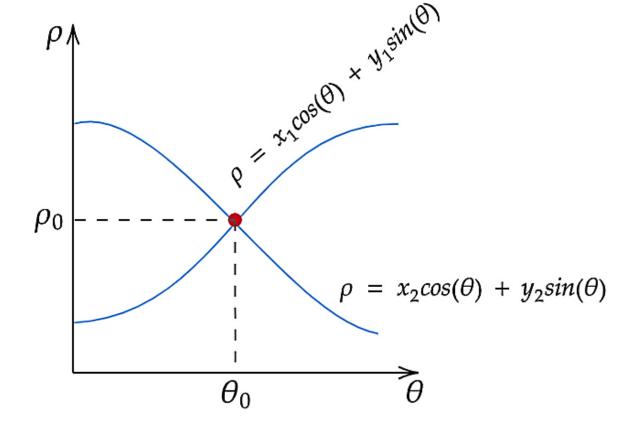
$$\theta = 90^{\circ}$$

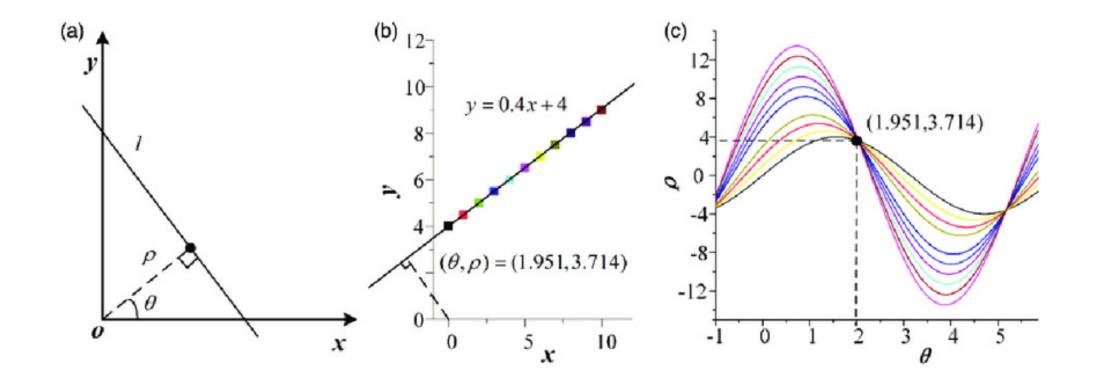
- Ranges:
  - $\theta \in [-90^{\circ}, 90)$
  - $\rho \in [-dmax, +dmax]$
  - o dmax?

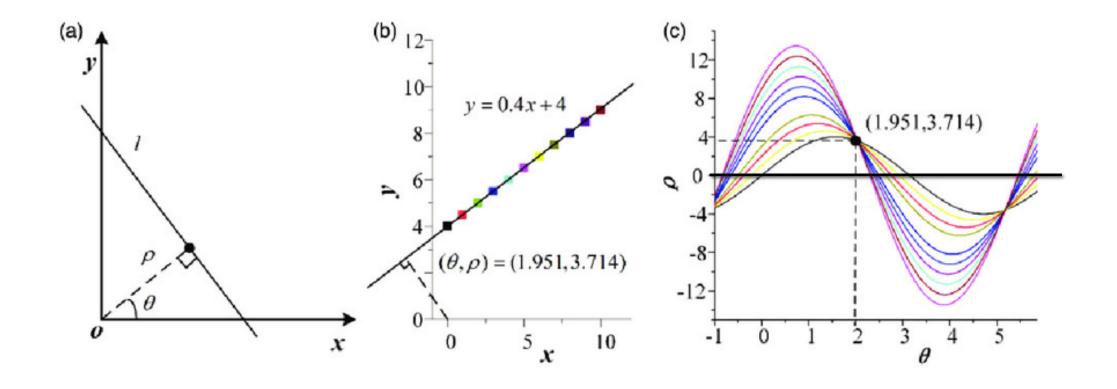




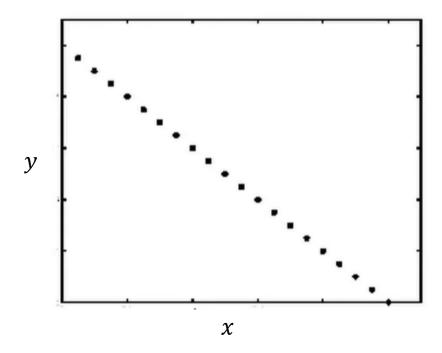




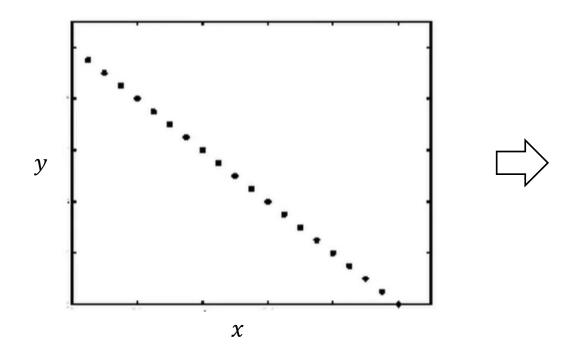




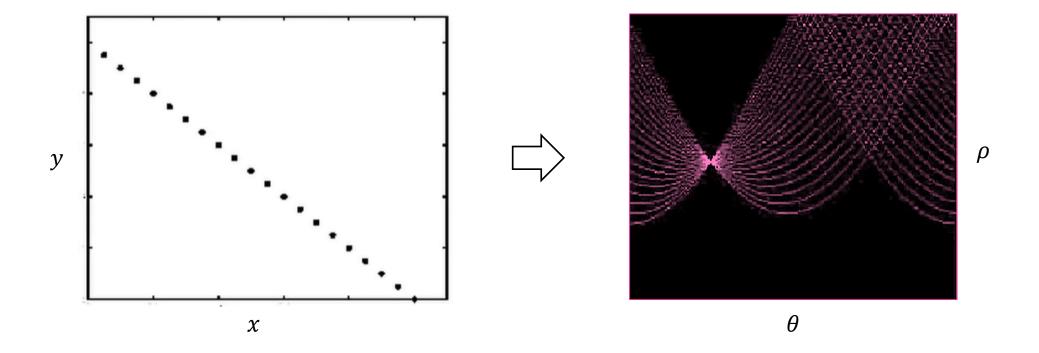
HT example:



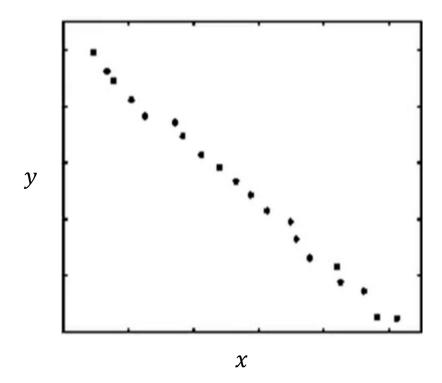
HT example:



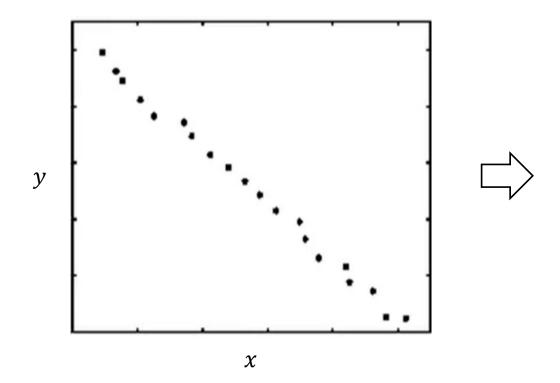
HT example:



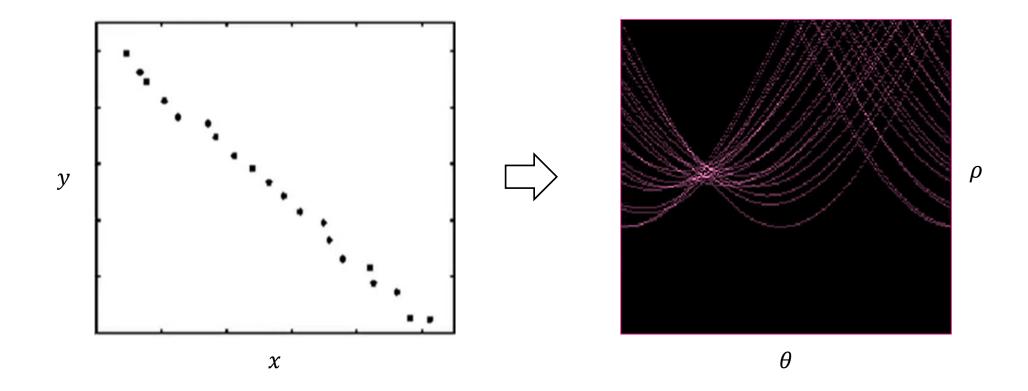
HT example: with a greater noise



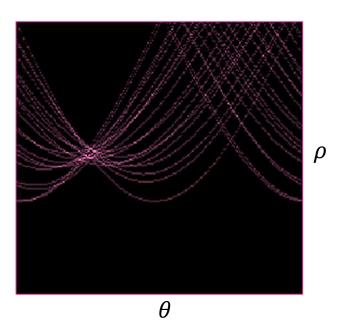
HT example: with a greater noise



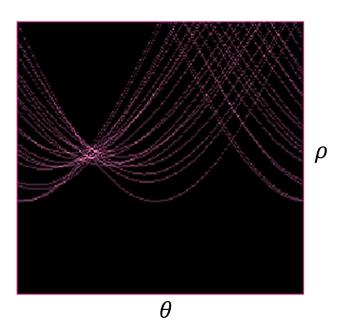
HT example: with a greater noise



- HT example: with a greater noise
  - tackling the noise

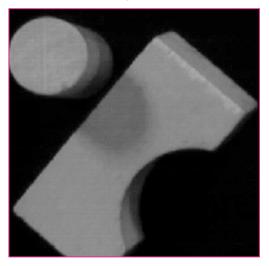


- HT example: with a greater noise
  - tackling the noise

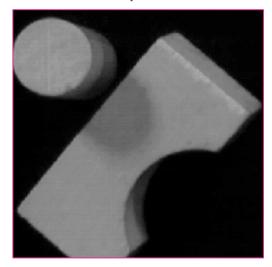


- Image processing in the Hough space
  - smoothing
  - thresholding
  - zoom in the space
  - o re-quantize zoomed space
  - redo HT in zoomed space

input



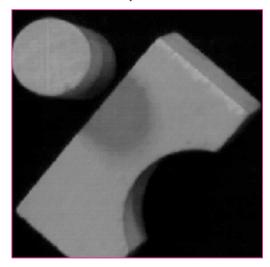
input







input



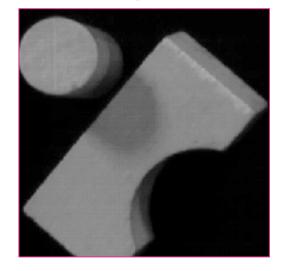


Hough transform



bright spot in HT corresponds to?

input



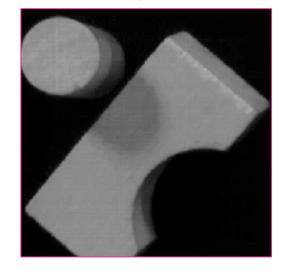


Hough transform



- bright spot in HT corresponds to?
- can circles be detected?

input



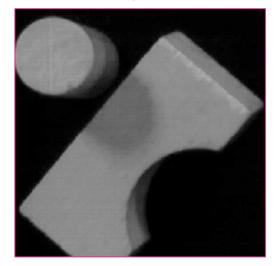


Hough transform



- bright spot in HT corresponds to?
- can circles be detected?
- why does Hough image is not the same size as input?

input





Hough transform



#### Input



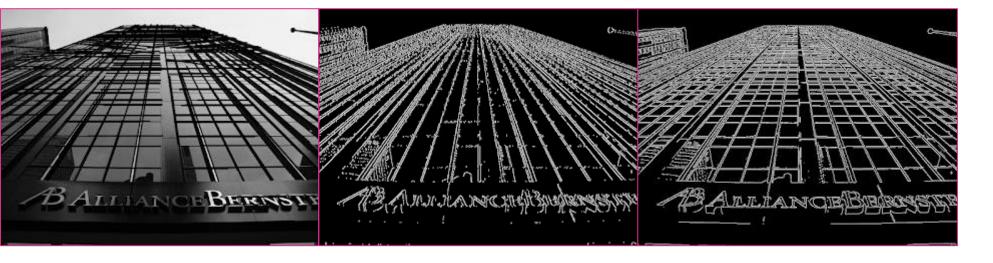
#### Input

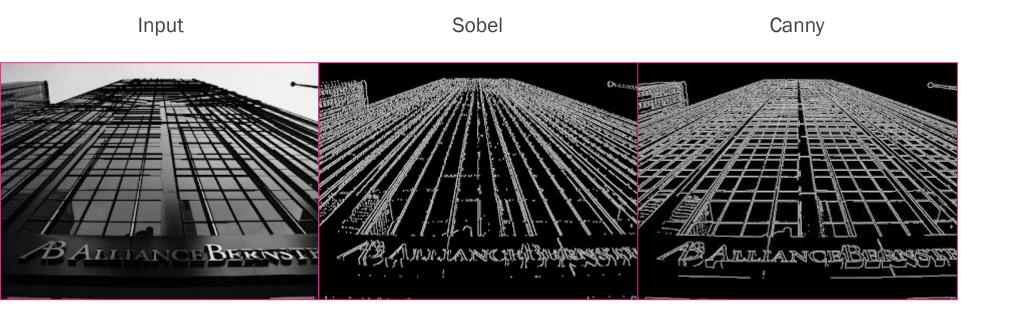


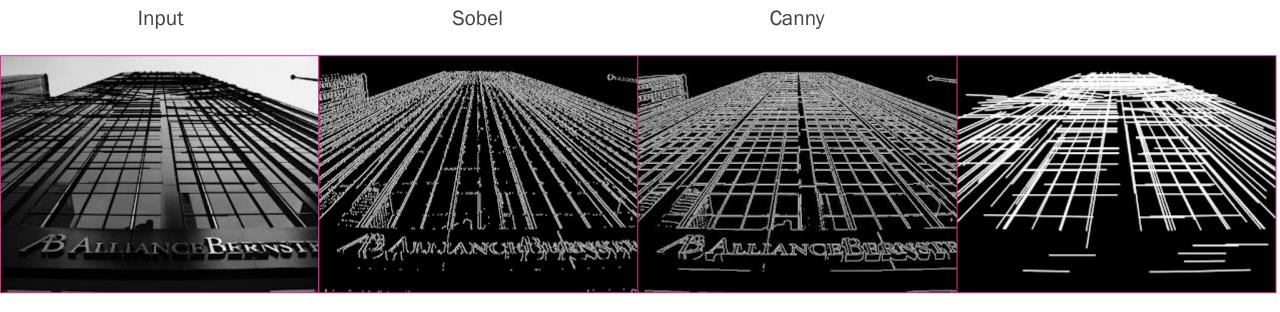
Input Sobel

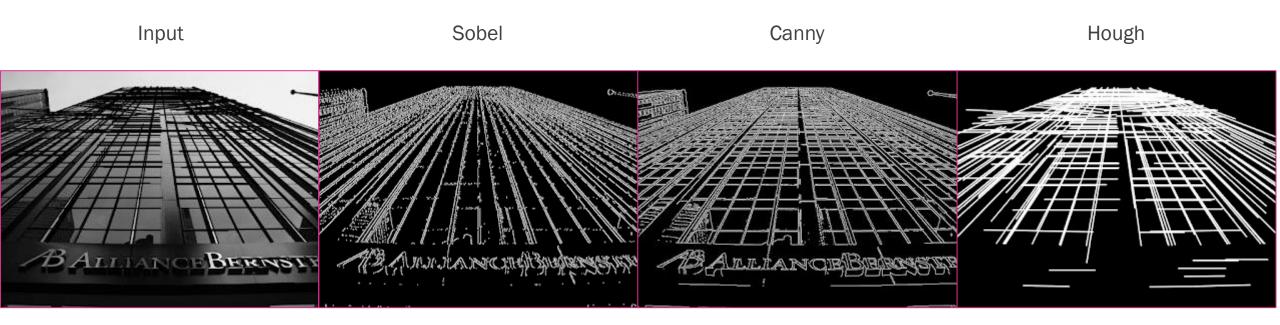


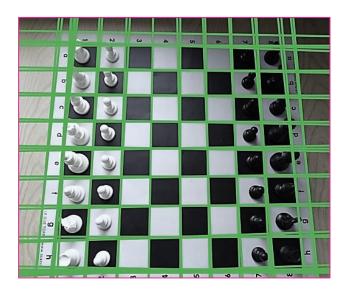
Input Sobel

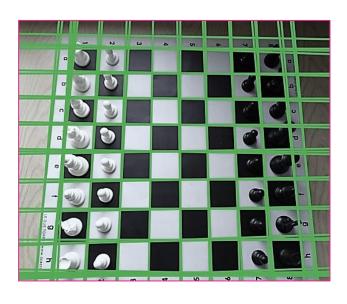




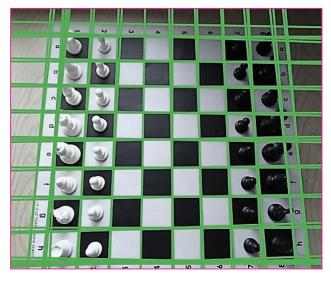






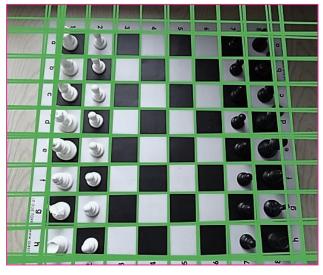










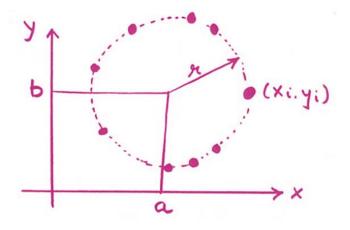








Equation of circle

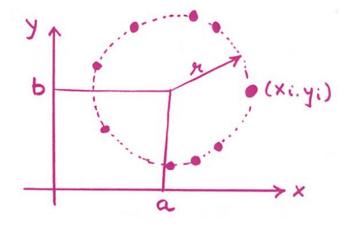


Equation of circle

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

If radius is known: (2D Hough Space)

Accumulator Array A(a,b)

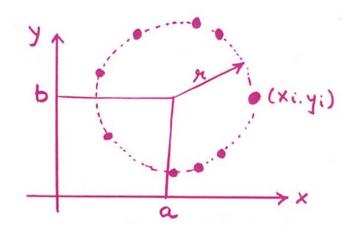


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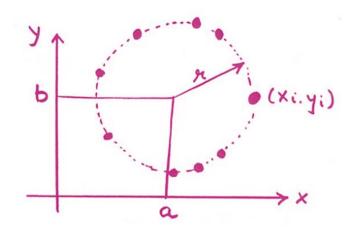
- Approx. object's size are known
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Equation of circle

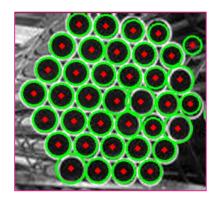
$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

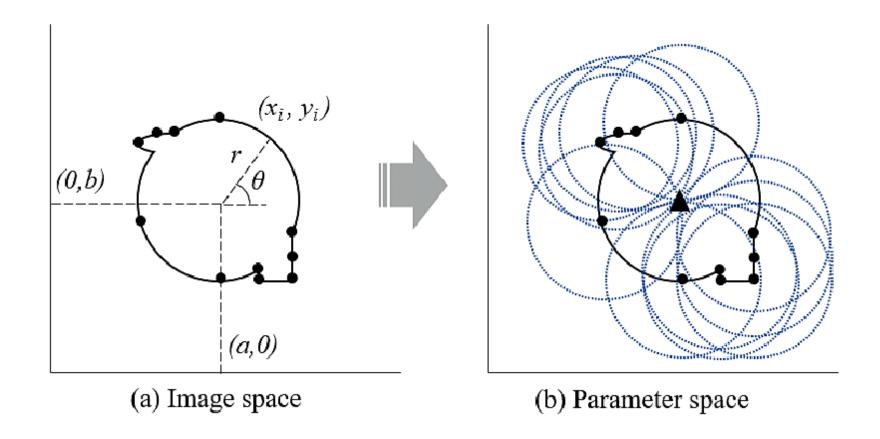
If radius is known: (2D Hough Space)

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- If radii are not known, exhaustively search all possibilities
- Pseudocode:

```
: A( ) = 0

: \forall (x, y)

: if M_T(x, y)

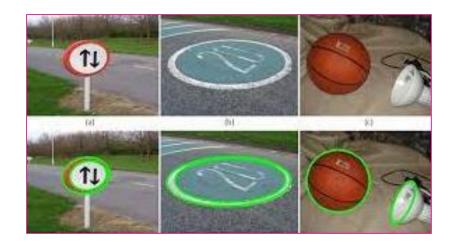
: \forall (a, b)

: r = sqrt\{ (x - a)^2 + (y - b)^2 \}

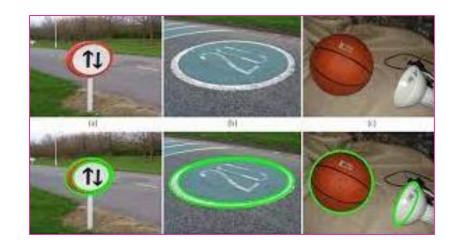
: A(a, b, r) + +

: find \ maximas \ in \ A( )
```

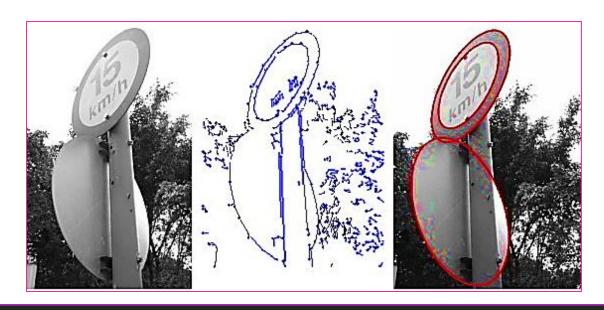


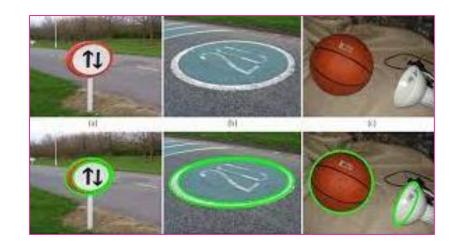






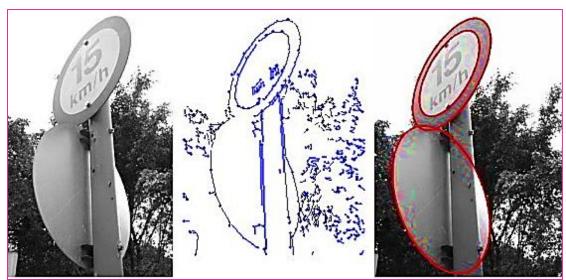




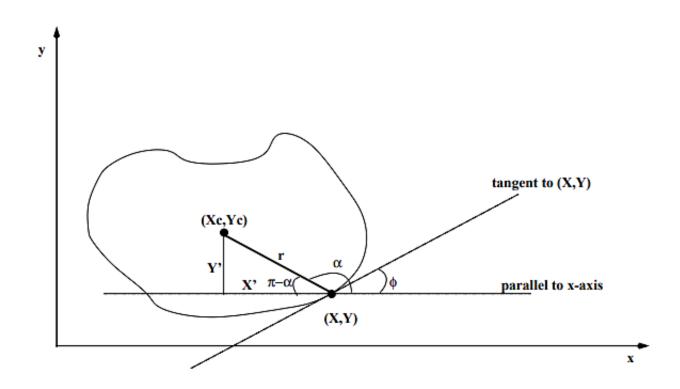






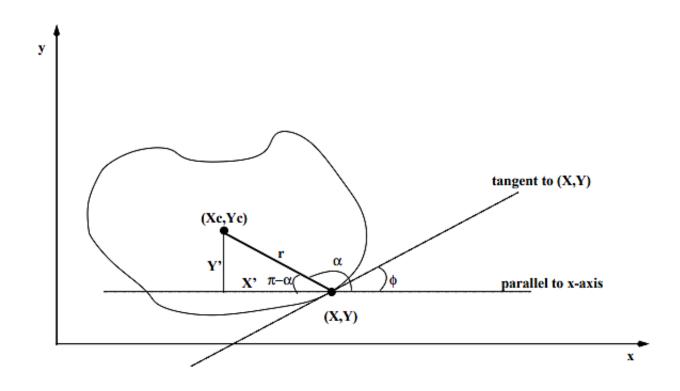


For any arbitrary shape



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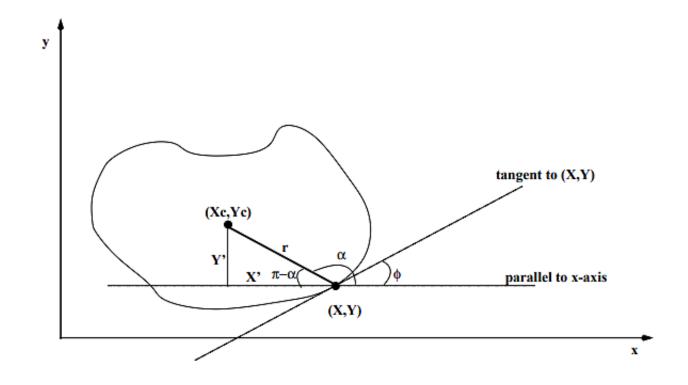
$$x = x_c + x'$$
 or  $x_c = x - x'$   
 $y = y_c + y'$  or  $y_c = y - y'$ 



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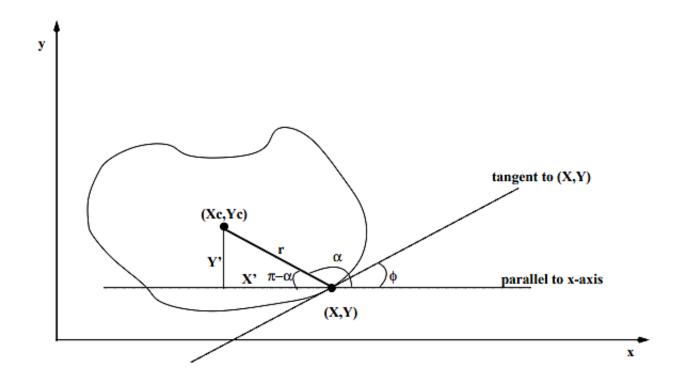
x'



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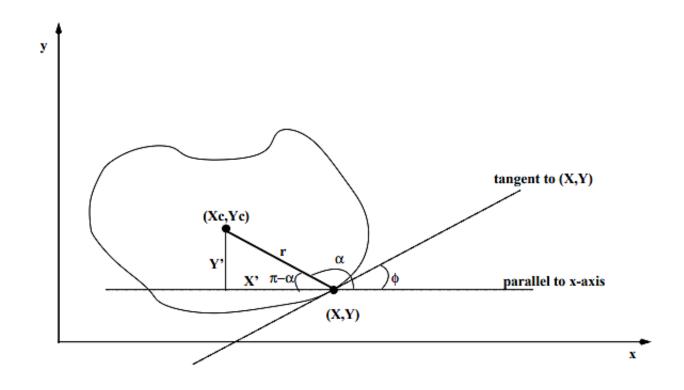
$$x' = rcos(\pi - \alpha) = -rsin(\alpha)$$



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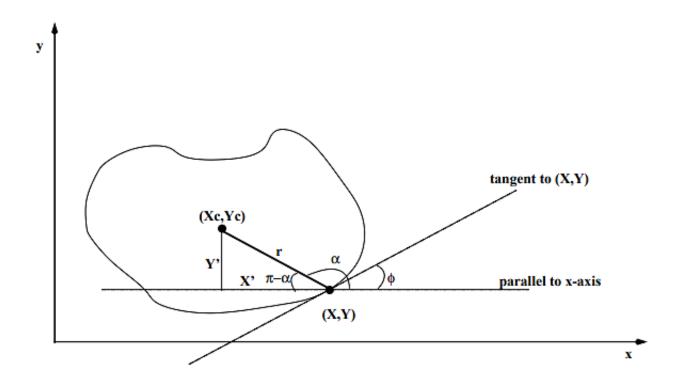


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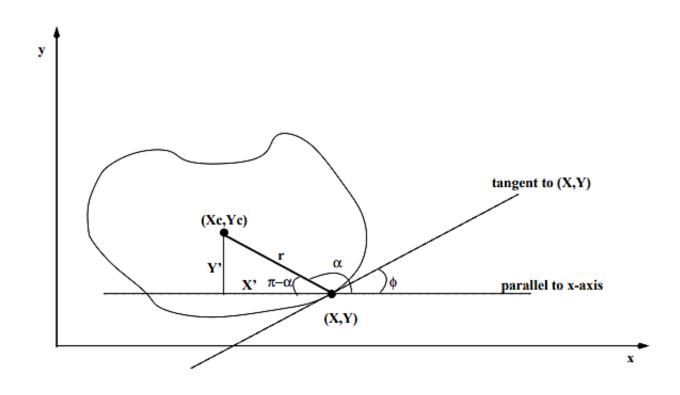
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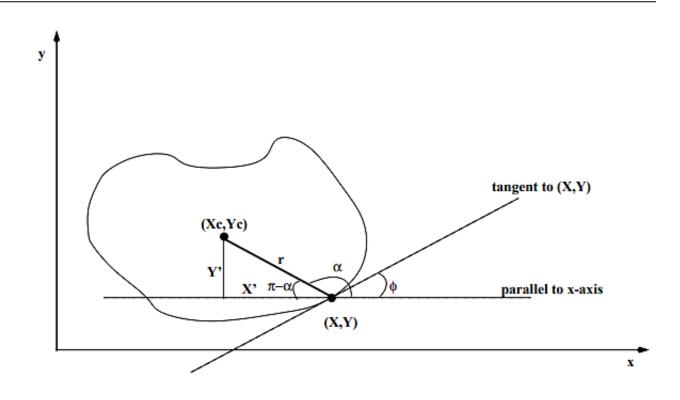
For any arbitrary shape

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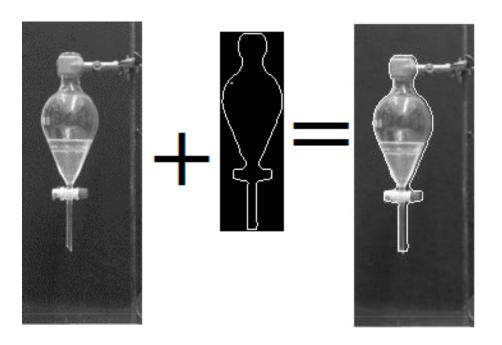
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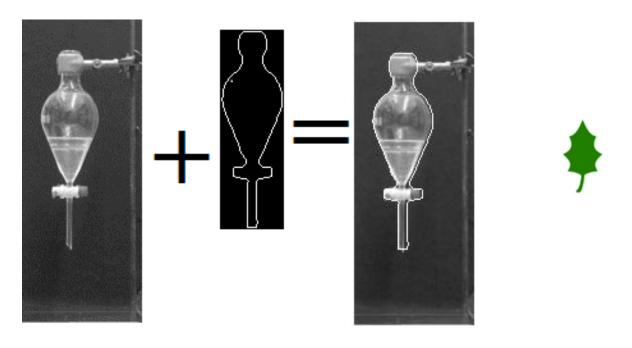


Edge Direction	$\vec{r} = (r, \alpha)$
$\phi_1$	$\vec{r}_1^{\ 1}, \vec{r}_2^{\ 1}, \vec{r}_3^{\ 1}$
$\phi_2$	$\vec{r}_{1}^{2}$ , $\vec{r}_{2}^{2}$

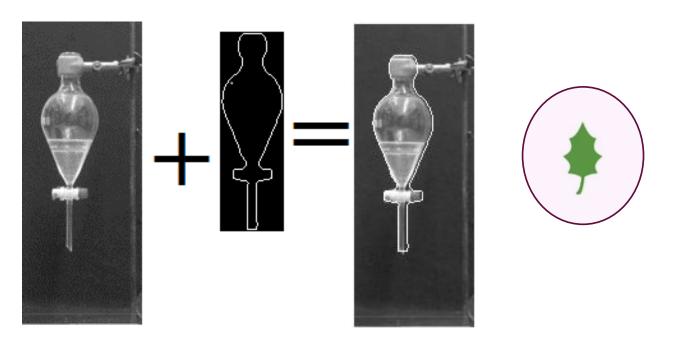
Ref: Mathworks & prof Nayar

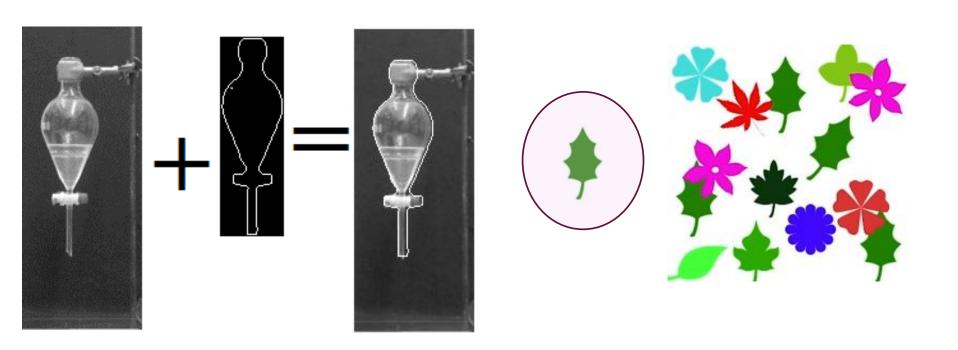


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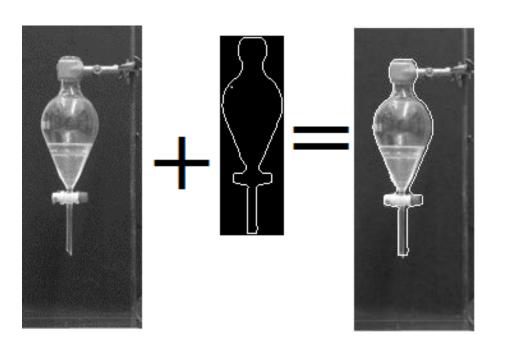


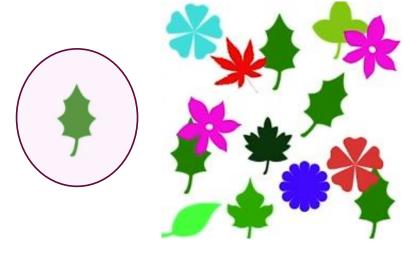
Ref: Mathworks & prof Nayar

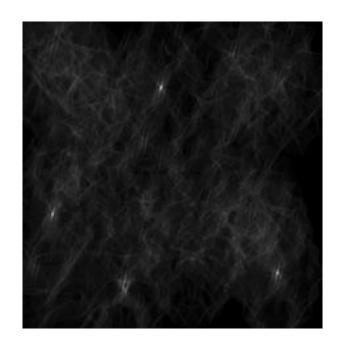




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  - With k quantized bins, it exponentially increases with number of parameters  $n \rightarrow k^n$

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Time complexity

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  - Separate quantization for each dimension can be performed

- Time complexity
  - Voting is linearly proportional to # of edge points
  - Time complexity is constant in # of edge points detected

# Hough transform: other shapes

	parameters	
Line	ρ, θ	xcosθ+ysinθ=ρ
Circle	x <sub>0</sub> , y <sub>0</sub> , ρ	$(x-x_0)^2+(y-y_0)^2=r^2$
Parabola	x <sub>0</sub> , y <sub>0</sub> , ρ, θ	$(y-y_0)^2=4\rho(x-x_0)$
Ellipse	$x_0, y_0, a, b, \theta$	$(x-x_0)^2/a^2+(y-y_0)^2/b^2=1$

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- Hough Transform

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Hough Transform

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